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Patrick Aubert† Eve Caroli‡ Muriel Roger§

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Abstract

This paper investigates the relationships between new technologies, innovative workplace practices and the age structure of the workforce in a sample of French manufacturing firms. We find evidence that the wage-bill share of older workers is lower in innovative firms and that the opposite holds for younger workers. This age bias affects both men and women. It is also evidenced within occupational groups, thus suggesting that skills do not completely protect workers against the labour-market consequences of ageing. More detailed analysis of employment inflows and outflows shows that new technologies essentially affect older workers through reduced hiring opportunities as compared to younger workers. In contrast, organisational innovations mainly affect the probability of exit, which decreases much more for younger than for older workers following reorganisation.

Keywords: new work practices, technology, older workers, labour demand.

JEL classification: J23, L23, O33

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Introduction

In response to increasing national and international competition, many American and European firms have invested in information technologies (IT) over the past three decades. Along with the introduction of computer systems and network technologies, most firms have reorganised their workplace in order to introduce more flexible organisational devices. These include self-managed teams, multi-tasking, just-in-time production and delivery, total-quality management and some decentralisation of decision making. They are often referred to as "high performance" workplace practices.

One important question regarding technological and organisational innovations has to do with their labour-market consequences: do they affect the structure of employment and, as a consequence, do they hurt the employment prospects of particular types of workers? Evidence in the literature suggests that both technological and organisational innovations are biased against unskilled labour. As regards technological change, there is a general agreement that the development of IT has reduced the employment opportunities of less skilled workers (see Chennells and Van Reenen (2002) for a review). The literature on organisational change is more recent, but several works suggest that innovative workplace practices have also been detrimental to lower skilled employment in various countries - see Caroli and Van Reenen (2001) and Bresnahan *et al.* (2002).

One related issue we tackle here is: are new technologies and workplace practices biased against age? In other words, do they hurt the employment prospects of older workers, respective to younger ones? This question is of particular relevance in Europe given that the population is ageing fast and that the employment rate of older workers is particularly low: no more than 40% of the population aged above 55 is employed in Europe, as compared to 58% in the USA and 62% in Japan. From a policy point of view, the extent of the problem is such that, in 2001, the European Council has set up the so-called "Stockholm target", aiming to increase the employment rate of workers aged 55-64 to 50% by 2010.

In analysing the reasons for the low employment rate of older workers, the supply side dimension has long been put forward (Gruber and Wise, 2004). However, one can wonder whether demand side considerations could also be at play, in particular in a context of rapid technological and organisational changes (OECD, 2005). The relationship between IT adoption and work reorganisation on the one hand and the age structure of the workforce on the other hand is, a priori, uncertain. Technological and organisational innovations may be positive for older workers because they are more skilled and experienced. Given that both types of innovations are skill biased, one could expect new technologies and workplace practices to be favourable to older workers.

On the other hand, innovation may negatively affect older workers through two different effects. First, if it accelerates *skills obsolescence*, the productivity of older workers relative to younger ones will decrease since part of their competences will be outdated. Since Rosen (1975), the literature traditionally distinguishes between two types of obsolescence: technical skills obsolescence (or internal depreciation of human capital) corresponds to the reduction in the volume of human capital, whereas economic skills obsolescence (or external depreciation) corresponds to the decrease in the market value of a given stock of human capital. Technical skills obsolescence is likely to be caused by physiological factors such as ageing, injuries or illnesses, or by the lack of use of skills. Economic skills obsolescence results from changes in the market value of skills, possibly caused by technological and organisational innovations (de Grip and van Loo, 2002). Second, technological and organisational innovations may negatively affect older workers through *adaptability* requirements. Both technological and organisational changes bring about important transformations in the production process which require that workers adapt to a new environment. Workers have to adjust to new technologies and equipments and to an organisation of work based on multi-skilling in which they are awarded greater autonomy and responsibility. Moreover, the working environment tends to change more rapidly than it used to, both because of increasing technological obsolescence and because of the constant redefinition of tasks to be performed. So, workers are required to be flexible and to adapt to frequent changes in the content of their job and in the production process they have to operate. An important literature in cognitive sciences suggests that, as people age, they become less skilled at adapting to changes[1] (Bosma *et al.*, 2003). If this is the case, older workers may be partly substituted by younger ones in most innovative firms.

The consequences of new work practices in terms of multi-skilling and adaptability requirements are underlined by Borghans and ter Weel (2005) in this *Feature*. They model the internal organisation of firms as the result of a trade-off between the benefits of specialisation - namely, higher returns to the time spent on tasks when workers perform a narrower range of them - and the costs of communication - between workers or teams of workers performing different sets of tasks. Any increase in the effectiveness of communication due to the introduction of IT then results in an increase in the number of teams, with each team being more specialised, i.e. per-

[1]We thank Richard Murnane for drawing our attention to this point.

forming a smaller range of tasks. In contrast, when investment in IT brings about a reduction in production time, coordination costs become a major concern. So, the optimal organisation of work becomes more generic with teams of workers performing a greater variety of tasks. According to the empirical analysis carried out in the paper, the productivity effect dominates, so that the organisation of work tends to increasingly rely on multi-skilled workers. By definition, multi-skilling requires a strong adaptability on the part of workers. One consequence of this is that new technologies and innovative workplace practices are found to be skill biased. Borghans and ter Weel show that more computer adoption leads to a more generic work organisation and to a higher share of skilled workers. In what follows, we investigate the existence of another possibly *age related* bias due to the fact that older workers are less able to adapt to the new technological and organisational environment.

The idea that technological innovation may negatively affect older workers has been tested in various ways in the literature. A first strand of papers checks whether older workers have difficulty using computers. In general, evidence of such difficulty is not compelling. Borghans and ter Weel (2002) find virtually no impact of age on individual computer use once controlling for tasks. Friedberg (2003) finds partial evidence of skills obsolescence, with technological change in a worker's environment having a negative impact on computer use, but only for workers close to retirement. From this first group of studies, older workers do not appear to lag behind systematically in terms of computer use. One problem in this literature is, of course, selection bias. The probability of using a computer is measured on a sample of workers who all are in employment. However, it is quite likely that workers who are still employed when they get old be the most efficient and that this correlates with computer use. If this is the case, the impact of age as estimated in this literature will be underestimated, given that most unable workers will have already retired or been laid-off.

A second empirical strategy has therefore consisted in estimating the impact of computer use on retirement decisions. Bartel and Sicherman (1993) show that workers in industries with a higher average rate of technological change[2] tend to retire later. However, unexpected changes in the rate of technological change[3] induce workers to retire earlier. This suggests that, in the short run, when technological innovations are introduced, older workers who feel they cannot adapt tend to retire. In the longer run though, technological change makes retraining more profitable

[2]The average rate of technological change is measured by ten year differences in the average annual rate of TFP growth.

[3]Unexpected changes are measured as the deviation from the permanent rate of technological change divided by the standard deviation over the past 10 years.

which, in turn, creates an incentive for workers in high-tech industries to retire later.

In this paper, the employment prospects of older workers in innovative firms are studied using firm-level data and investigating the relationships between new technologies, innovative workplace practices and the age structure of the workforce in France in the 1990s. More specifically, we investigate how the use of innovative devices affects the wage-bill share of various age groups within firms. We find evidence that the wage-bill share of older workers is lower in innovative firms and that the opposite holds for younger workers.[4] This is true both for men and women separately. This pattern of results also holds within occupational groups, thus suggesting that skills do not completely protect older workers against the labour-market effects of innovation. This anti-age bias of innovative firms is consistent with the general pattern of employment inflows and outflows. We find that new technologies enhance hiring opportunities for younger workers much more than they do for older ones. In contrast, the impact of organisational innovation is through exits. It decreases exits much less for older workers than for younger ones. This suggests that older workers may suffer either from skills obsolescence or from a lack of adaptability in a context of rapid technological and organisational changes.

The paper is organised as follows. Section 1 outlines the econometric model. Section 2 discusses the data. Results are presented in Section 3. Some concluding comments are offered in Section 4.

1 The Econometric Model

1.1 Wage-bill shares

To investigate the relationships between new technologies, innovative workplace practices and the age structure of the workforce, we start from a classical labour-demand framework, assuming that the cost function is a restricted translog. Since we are interested in age effects, the only variable inputs are different types of labour indexed by age a. Under these assumptions, it is straightforward to derive a system of wage-bill share equations for each age category a of the familiar form:

[4] The empirical strategy we propose here has been followed by Schöne (2004) and Beckmann (2004) in two recent papers. On Norwegian data, Schöne finds essentially no evidence of age bias in relation to innovation. Regarding computer use, he finds no effect on the wage-bill share of workers aged 50 and above. The effect on younger workers (aged 20-29) is even negative. Only workers in their 30s are positively affected. As for organisational change, it has no significant impact whatever the age group. In contrast, on West German data, Beckmann (2004) finds strong evidence of age-biased technological and organisational change. Both have a negative effect on the share of workers above 50 in employment and a positive effect on workers below 30.

$$S^*_{a,i,t} = \alpha_a + \sum_{a' \in \{1,...,A\}} \gamma_{a,a'} . \ln(W_{a'})_{i,t} + \gamma_{a,K} . \ln(K)_{i,t} + \gamma_{a,INNOV} . \ln(K^{INNOV})_{i,t} + \gamma_{a,VA} . \ln(VA)_{i,t} + \psi_{a,i,t}. \quad (1)$$

where $S^*_{a,i,t}$ is the static equilibrium wage-bill share of age category a in firm i at time t, K the stock of tangible capital (assumed to be a quasi-fixed factor), VA the value-added of the firm, $W_{a'}$ the wage rates of workers of age category a' and $\psi_{a,i,t}$ stochastic error terms. We also assume that there is a factor, K^{INNOV}, that captures the use of new technologies and high-performance workplace practices in firms (see Section 2). The total number of age categories is A.

Since we consider the system of wage-bill share equations for all age categories, we need to place further restrictions on the parameters. *Symmetry* implies that $\gamma_{j,j'} = \gamma_{j',j}$ for all j and j' in $J = \{a = 1, ..., A; K; VA;\ K^{INNOV}\}$. *Homogeneity* implies that we also have $\sum_{a=1,...,A} \alpha_a = 1$ and $\sum_{a=1,...,A} \gamma_{a,j} = 0$ for all j in J. Coupled with the fact that the shares add up to unity, one equation becomes redundant and we need only estimate the system for all age categories a but the first one. Our econometric model hence writes:

$$S^*_{a,i,t} = \alpha_a + \sum_{a' \in \{2,...,A\}} \gamma_{a,a'} . \ln(W_{a'}/W_1)_{i,t} + \gamma_{a,K} . \ln(K)_{i,t} + \gamma_{a,INNOV} . \ln(K^{INNOV})_{i,t} + \gamma_{a,VA} . \ln(VA)_{i,t} + \psi_{a,i,t} \qquad \forall a \in \{2, ..., A\}. \quad (2)$$

One problem with equation (2) is that error terms $\psi_{a,i,t}$ may be correlated for different age categories within the same firm at the same period of time. Therefore, in a standard regression, the shape of the covariance matrix of the $\psi_{i,t} = (\psi_{2,i,t}, ..., \psi_{A,i,t})$ vector has to be taken into account in order to improve the efficiency of the estimation. This can be performed by using a joint generalised least square (JGLS) estimator. In the present case, we first perform an OLS regression and use the residuals to estimate the cross-equation covariance matrix used in the second step.

A second problem has to do with unobserved heterogeneity. A usual way to tackle the fixed effects problem is to estimate the model in long differences. However we cannot do so because our data has information on "innovativeness" (the K^{INNOV} variable) at only one year (see Section 2). In the absence of other instruments, we opt for estimating the labour-demand equations by JGLS and interpret the results as describing correlations rather than causal links.

1.2 Employment inflows and outflows

Wage-bill share equations provide an insight of how the age structure of the labour force varies across innovative and non-innovative firms. As a second step, we focus on inflows and outflows in order to determine whether the low demand for some age groups in innovative firms results in more separations or in reduced hiring opportunities.

Let $N_{a,i,t}$ denote the number of workers of age a in firm i at time t. $N_{a,i,t}^{HIRE}$ is the number of newly hired workers aged a in firm i at time t, and $N_{a,i,t}^{EXIT}$ the number of workers aged a leaving[5] firm i at year t. We define the share of entrants aged a in firm i at year t as $P_{a,i,t}^{HIRE} = \frac{N_{a,i,t}^{HIRE}}{N_{a,i,t}}$ and the share of workers leaving the firm as $P_{a,i,t}^{EXIT} = \frac{N_{a,i,t}^{EXIT}}{N_{a,i,t}}$. We assume that $P_{a,i,t}^{EXIT}$ and $P_{a,i,t}^{HIRE}$ can be written as:

$$P_{a,i,t}^{HIRE} = \alpha_a^{HIRE} + \beta_a^{HIRE}.\ln(K^{INNOV})_i + X_{i,t-1}.\gamma^{HIRE} + Z_{i,t-1}^{A}.\delta^{HIRE} + \varepsilon_{a,i,t}^{HIRE}$$

and

$$P_{a,i,t}^{EXIT} = \alpha_a^{EXIT} + \beta_a^{EXIT}.\ln(K^{INNOV})_i + X_{i,t-1}.\gamma^{EXIT} + Z_{i,t-1}^{A}.\delta^{EXIT} + \varepsilon_{a,i,t}^{EXIT}$$

where $\ln(K^{INNOV})_i$ is our measure for innovative capital, $X_{i,t-1}$ is a set of labour-demand factors (relative wages, tangible capital, value-added, industry and size dummies) in firm i at time $t-1$, $Z_{i,t-1}^{A}$ is the vector of the employment shares of age groups, and $\varepsilon_{a,i,t}^{HIRE}$ and $\varepsilon_{a,i,t}^{EXIT}$ are stochastic error terms. The main advantage of such a linear model is that it enables us to estimate the share of entries and exits for all age groups simultaneously, using JGLS, thus allowing to take into account potential correlations between entries and exits across age groups.

Since we are interested in hiring opportunities and incidence of separations for older workers relative to younger ones, we decompose β_a^{HIRE} into two components: θ^{HIRE} that is common to all workers, and an age-specific component θ_a^{HIRE} (resp. θ^{EXIT} and θ_a^{EXIT} for β_a^{EXIT}). We constrain the θ_a^{HIRE} (resp. the θ_a^{EXIT}) to add up to zero to make the model identifiable:

$$\beta_a^{HIRE} = \theta^{HIRE} + \theta_a^{HIRE} \quad and \quad \beta_a^{EXIT} = \theta^{EXIT} + \theta_a^{EXIT}, foralla$$

i.e.

$$\theta^{HIRE} = \frac{\sum \beta_{a'}^{HIRE}}{A} \qquad and \quad \theta_a^{HIRE} = \beta_a^{HIRE} - \frac{\sum \beta_{a'}^{HIRE}}{A}$$

where A is the total number of age groups.

[5]Exits include workers who are fired, who retire, ends of short-term contracts and workers who leave the firm on a voluntary basis (either by resigning or on early retirement schemes). Unfortunately, our data do not allow us to distinguish between these various forms of exits.

2 The data

The data we use come from several databases since we need to combine information on technology and workplace organisation, on the age and skill structure of the workforce, and on the level of capital and value-added. One rich source of information on new technologies and workplace organisation in France is the COI (*Changements Organisationnels et Informatisation*) survey. It was carried out at the end of 1997 and covers 4,283 firms with more than 20 employees in the manufacturing sector. Senior managers were asked questions about computer use and firm organisation as of 1997.

As the COI survey does not include data on the age structure of the workforce nor on wages, we draw on a second database, namely the DADS file (*Déclarations Annuelles de Données Sociales*) in order to examine wage-bill shares for various age groups. This is an exhaustive dataset available on a yearly basis. It is built out of employers' mandatory reports and covers all employees of all firms in the French private sector. The DADS file provides information on the size of the firm and on the sector in which it operates. For each employee, it also provides information on hours and days worked during the past calendar year, gross earnings, age and occupation. In addition, the DADS provides information on labour flows, by allowing to know whether employees have been entering or leaving the firm during the past calendar year.[6] Eventually, we find information on the financial structure of firms in a third database, namely the BRN (*Bénéfices Réels Normaux*). This database consists of firms' balance sheets and is collected by the tax administration. It includes some 600,000 firms in the private non-financial non-agricultural sectors each year and covers about 80% of total sales in the economy. This file provides us with a measure of value-added and physical capital.[7]

Matching the DADS and BRN with COI and cleaning out firms with implausible changes in the total wage bill[8] reduces the sample to 3,816 observations in 1998. When analysing employment inflows and outflows, we use a larger dataset: we allow labour adjustments to take time, and thus pool our data over 1998-2000. We jointly estimate employment flows for all age groups in each firm. So, we restrict our sample to firms with at least one worker in each age group over the period. Eventually, we only keep firms with both inflows and outflows given that

[6]Entrants are defined as workers who are in an establishment of the firm at t and were not there at $t-1$ and, in a symmetric way, workers leaving the firm are those who were employed in an establishment of the firm at t and are not there at $t+1$. For the sake of consistency we eliminate firms for which the number of workers reported for t in $t+1$ differs from the number reported in t.

[7]Physical capital is defined as the stock of fixed assets registered at their historical costs.

[8]We eliminate firms for which the change in the total wage bill between year $t-1$ and year t is greater (or less) than its average value plus (or minus) five times its standard deviation. This reduces the sample by at most 2.5%.

it makes little sense to study the relative employment flows into/out of the various age groups if there is no entry nor exit in a firm. This leaves us with 3,336 firms in 1998, 3,185 in 1999 and 3,053 in 2000.

Our dataset includes rich information on technology and workplace organisation, on the age and skill structure of the workforce, and on the level of capital and value-added. Regarding age, we consider four age groups: [20 to 29], [30 to 39], [40 to 49], and [50 to 59] years old. We do not consider workers aged 60 and above since, until 2003, legal retirement age in France was 60 so that firms' demand was not the main motivation for employment changes beyond that age.

Regarding innovation (our K^{INNOV} variable), we define three technological and organisational indicators. The COI database asks firms' senior managers about the proportion of workers using computers in several occupational groups. We use this information to construct a binary variable, $COMP$, equal to 1 if more than 40% of workers use computers in at least two occupations. $COMP$ is equal to 1 for 75% of the firms in the sample. Following Crépon *et al.* (2003), we define a second indicator of technological intensity: $INET$ is equal to one when the firm uses the Internet either to have access to email or to advertise or collect information. This indicator is equal to 1 for 40% of the firms, and both $COMP$ and $INET$ are used simultaneously by 36% of the firms. In addition to technology, the COI survey provides very rich information on workplace organisation. Firms are asked whether they use quality norms, self-managed teams and quality circles, just-in-time production or delivery, multi-tasking, total-quality management, whether delayering has taken place over the past three years etc. We build up a summary indicator of the use of innovative workplace practices, $ORGA$, defined as the sum of 13 different organisational devices. Thus doing, we consider that firms which have adopted a large number of these workplace practices are more innovative than firms which have adopted only a few of them. As compared to what is usually done in the literature, where organisational innovation is most often measured through binary variables (see Black and Lynch, 2001), the main advantage of our indicator is that it partially captures the intensity of organisational innovativeness.

13.3% of the firms in our sample use one innovative organisational practice and the proportion decreases as the number of devices goes up, down to 0.7% of firms using all 13 devices (See Table 1). Not surprisingly, organisational innovativeness is lower in smaller firms (51% of the firms using 0 organisational devices have less than 50 employees) and higher in bigger ones (all 27 firms using 13 organisational devices have more than 200 employees).[9] Moreover, our three innovation indicators appear to be positively correlated: the average rates of computer and Internet use

[9]Complete tables of descriptive statistics are avalaible from the authors upon request.

steadily increase with the number of innovative organisational practices at work within firms.

The correlation between the use of new technologies or innovative workplace practices and the wage-bill shares of workers within firms varies according to the age groups (see Table 2). The correlations between computer use or the intensity of organisational innovativeness are negative and significant, at least at the 10% level, for workers above 50 years old. Results are less sharp for other age groups. However, the share of workers aged 40-49 appears to be positively correlated with the use of new organisational devices and the same goes for computer use and the share of workers aged 30-39. As regards men an women, IT and innovative workplace practices are correlated with a greater share of men of all ages in the wage bill and correspondingly a lower share of women. The age pattern of correlations is not so clear for men, whereas for women all three innovation indicators appear to be more strongly (negatively) correlated with the share of older women than with the share of younger ones. When coming to the occupational structure of the workforce, indicators of IT and innovative organisational practices are positively correlated with the share of managers in the wage bill, and negatively correlated with that of clerks and blue-collars. Here again, the age pattern of correlations is not clear, except in the managerial group where the positive correlation between our three innovation indicators and the wage bill share appears to decrease in strength as age increases.

Correlations are much more significant when we focus on inflows and outflows, even if the values of the coefficients remain quite low. Apart from the correlation between Internet use and the inflow of younger workers (aged 20-29) which is positive and significant, all other correlations are either negative or insignificant. Both inflows and outflows appear to be lower in firms using new technologies and innovative workplace practices, thus suggesting that innovation reduces labour turnover. Moreover, the relative impact of innovation variables on employment inflows and outflows varies according to the age groups.

The relationships between innovation variables on the one hand, and the wage-bill shares and employment inflows/outflows by age group on the other hand have been computed so far without controlling for firms characteristics and without taking into account the fact that labour demand may be correlated across age groups within firms. The regression analysis that follows deals with both issues.

To complete our data description, a number of descriptive statistics relative to wage-bill shares and inflows/outflows are provided in the Appendix Table.

3 Results

3.1 Wage-bill share estimates

3.1.1 Wage-bill shares by age group

We first jointly estimate the wage-bill shares for all age groups but the first one in 1998. Coefficients for workers aged 20-29 are estimated using the following homogeneity condition:

$$\gamma_j^{20-29} = -(\gamma_j^{30-39} + \gamma_j^{40-49} + \gamma_j^{50-59})$$

with $j \in J = \{K; VA;\ COMP, INET, ORGA\}$. Basic controls include four size and five industry dummies, along with the logs of value-added, physical capital and relative wages.

Table 3 presents the results for wage-bill shares estimated by JGLS in our basic specification. Firms that intensely use computers have a greater share of workers aged 30-39 in their wage bill and a lower share of workers aged 50 and above. The impact of the Internet is very similar, both in terms of magnitude and significance, with innovative firms spending a greater share of their wage bill on workers in their thirties and a lower share on the oldest age group. Concerning the use of innovative workplace practices, they also tend to be positively correlated with the wage-bill share of younger workers and negatively correlated with that of older workers. Workers aged below 40 are positively affected in firms using new organisational practices whereas the opposite holds for workers above 50.

The magnitude of these effects is not very large, though. When significant, absolute changes in the shares vary from 0.2 to 1.3 percentage point according to the age group. However, given the initial age structure of the workforce in our sample, such figures correspond to changes by 1 to 5.5% in the wage-bill shares of the various groups for each type of technological and/or organisational innovation used by the firm. Overall, the effect of being employed in an innovative rather than non-innovative firm is likely to be non negligible for workers aged 30-39 and 50-59, all the more that some 74% of the firms in our sample combine several types of innovation.

This anti-age bias of innovative firms is robust to a number of specification tests. Including fifteen rather than five industry dummies for the manufacturing sector[10] does not change the general pattern of the results for computer use and innovative workplace practices. In both cases, workers below 40 account for a larger share of the wage bill in innovative firms and the opposite holds for workers aged 50 and above. However, the use of the Internet stops being significant thus suggesting that this variable used to capture sectoral characteristics. Re-running regressions similar to those in Table 3 for employment rather than wage-bill shares yields

[10]This corresponds to a 36 (rather than 16) post industry classification for the whole economy.

somewhat weaker results, but the general pattern of effects remains unchanged. Older workers are negatively affected in firms using innovative workplace practices, while workers aged 30-39 are positively affected in firms using computers and the Internet. Another important issue has to do with the fact that innovative firms may reduce employment, with downsizing mainly affecting older workers for reasons independent from any skills obsolescence or adaptability consideration. This is the case if separation costs tend to be lower for older workers, for example due to the existence of early retirement schemes[11] or to the firing of older rather than younger workers being socially more "acceptable". Controlling for changes in firm employment over 1994-1997 leaves our results unchanged as compared to the basic specification, thus suggesting that the anti-age bias of innovation that we find is not entirely due to downsizing.[12]

Eventually, results in Table 3 indicate that more capitalistic firms have a greater share of workers above 40 years old in their wage bill and a lower share of workers aged 20-29. This is consistent with what is found by Aubert and Crépon (2003) and is likely to be due to the fact that older workers are more numerous in older firms which are also more capitalistic. In contrast, the value-added of the firm does not significantly impact the wage-bill shares of any age group.

Overall, innovative firms appear to be biased against older workers. Workers aged 50 and above account for a lower share of the wage bill - and to a lower extent, of employment - in firms using new technologies and/or innovative workplace practices, whereas the opposite holds for workers below 40.

3.1.2 Wage-bill shares by age and gender

One may wonder whether the negative impact of innovation affects both older men and older women in the same way. In manufacturing, men represent the larger share of employment, accounting for 76% of the workforce in our sample. This share might be even higher if we distinguish between tasks, with women being concentrated in non-production tasks while men are over-represented in production. Since tasks are different across gender, skills obsolescence

[11]The overall age structure of separation costs is a priori uncertain in France because firing costs tend to be lower for younger workers, but the existence of widespread early retirement schemes makes separation much cheaper for workers above 55.

[12]The same result holds if we control separately for growth and decline in employment. Employment growth is associated with a higher share of workers below 40 while employment decline is associated with a higher share of workers above 40, but including these controls does not affect the significativity of innovation variables. Running separate regressions for growing and declining firms yields similar, though somewhat weaker, results. Coefficients for organisational innovation are unaffected when splitting the sample into the two groups of firms. Concerning IT variables, only computer use appears to be significantly age biased in firms that decreased employment between 1994 and 1997, whereas the Internet is the only significant age-biased factor in firms that increased employment.

and adaptability problems may also be different, so that IT and organisational change may not impact men and women in the same way. In particular, a common idea in the literature is that relative-demand shifts have been most unfavourable to older men. This is of course partly due to the relative decline of the manufacturing sector, but other factors may be at work. Innovation is one of them. In order to uncover whether older men have particularly suffered from technological and organisational innovations, we estimate wage-bill shares by age and gender groups (see Table 4). These regressions yield the average difference in the share of men and women between innovative and non-innovative firms, as well as the differential impact of each type of innovation upon each age group within both gender groups. So, the overall effect of innovation on the wage-bill share of an age-by-gender category is the sum of the average gender effect and the differential age effect.[13]

Computer use is associated with a significantly higher share of men in the workforce. This might be due to the type of tasks involved and to the fact that there is a larger share of men in highly skilled occupations (see section 3.1.3). Once this average difference in the proportion of men and women is controlled for, the differential effect of computer use is negative and significant for workers aged 50-59 both among men and women. Correspondingly, it is positive for both younger men and younger women, although this positive impact appears to occur slightly later in their careers for younger men (at 30-39 years old) than for younger women (at 20-29 years old).

Concerning the Internet, differences across age only show up among women, with a negative differential impact on the two oldest groups. However, since the average effect of the Internet on the share of women is positive and significant, the total effect of Internet use on older women is either positive or close to zero. In other words, this type of innovation positively and significantly benefits women in their 30s, while remaining neutral to older ones. Contrary to what happens for women, there is no significant differential impact of Internet use on age among men. This may stem from the fact that Internet use mainly affects non-production workers. Since a large proportion of men work in production tasks in manufacturing, this might explain why differences across age are not significant in this group.

As regards innovative organisational practices, both men and women above 50 are negatively and significantly affected. Concerning younger workers, men below 40 are positively affected, while there is no significant difference across age groups among women below 50 years old.

[13] Presenting the two effects separately in Table 4 permits to check directly whether the differential effect relative to the average is significant for each age category.

From this set of results, the anti-age bias of innovation seems to hold for both men and women, with no gender group being protected against it.

3.1.3 Wage-bill shares by age and occupational groups

Another interesting question regarding the age impact of innovation is whether it is uniform across occupations. Evidence in the literature shows that new technologies and organisational devices are biased in favour of workers in more highly skilled occupations. Are older workers more protected in such occupations or is the age bias independent from the skill dimension? In order to answer this question, we use the same kind of decomposition as for gender groups and estimate wage-bill shares by age and occupational groups (see Table 5). Once again, the regressions yield the average difference in the share of three occupations (managers and technicians, clerks, and blue-collars) between innovative and non-innovative firms, as well as the differential effect of each type of innovation upon each age group within the occupation.[14]

Concerning computer use, the occupational effect appears to be consistent with results in the literature. Managers tend to be positively affected by innovation, whereas blue-collars are negatively affected. When controlling for the occupational structure, computer intensive firms still display a bias against older workers. Within the manager category, the differential effect of computer use is positive on workers aged 30-39, whereas it is negative on workers above 50 years old. One exception has to do with the youngest group (i.e. 20-29 years old) which has a negative differential effect in firms using computers. However, the overall effect remains positive and significantly higher for younger workers than for workers aged 50-59. The fact that the youngest group of managers benefits relatively less from computer use than the group of managers aged 30-39 may be due to the fact that our manager category includes both managers and technicians and that proper managers are likely to be quite few in the youngest age group. So, the negative differential effect we capture here could be on technicians rather than on managers really. This would be consistent with the strong positive differential impact we find on the 30-39 year-old group within the manager category, which may be driven by the impact of computer use on proper managers. Regarding clerks, the overall age effect displays a pattern very similar to that of managers: workers under 40 are, if anything, positively affected by computer use, whereas the opposite holds for older workers. In the blue-collar group, the differential impact of computer use is positive for the youngest group, whereas it is negative for workers in their 40s. As for workers aged 50 and above, computer use seems to have a positive differential effect on this

[14] Here again, the overall effect of innovation on the wage-bill share of an age-by-occupation category is the sum of the average occupational effect and the differential age effect.

group, meaning that the overall (negative) effect of technological innovation is smaller for them than for workers in their 40s. One possible explanation is that experience may partly substitute for the lack of educational skills. Another explanation is that selection has already taken place for those workers, so that only the most adaptable ones are still in employment.

As regards the Internet, the results are very similar to those obtained for computer use. The average effect appears to be positive for managers and clerks, and negative for blue-collar workers. Within each occupational category, younger workers tend to be positively affected while older ones are negatively impacted. However, the age limit varies according to the occupational group: only the oldest group (i.e., 50-59 years old) of clerks is negatively affected, whereas the negative effect of the Internet appears to be worsened by age for blue-collars, as soon as they turn 30. One exception is again young managers who seem to be negatively affected by the web, as well as the oldest group of blue-collars who would be positively affected. Once again, this regards only the differential effect on age. The overall impact of the Internet remains positive and significant for younger managers, while it is negative and significant for blue-collars above 50.

Concerning new organisational practices, the effect on the occupational structure does not come up as significant except for clerks where it is negative. However, the age effect of innovation is confirmed within occupational groups with workers below 40 being positively impacted in the managerial group and workers aged 50 and above being negatively affected both in the manager and blue-collar groups.

These results suggest that skills do not protect older workers against the anti-age bias of innovation.

3.2 Employment inflows and outflows

Another interesting question has to do with the impact of innovation on employment inflows and outflows. As already mentioned, one possible explanation of the behaviour of innovative firms with respect to older workers relies on downsizing, if the burden of the adjustment is disproportionately borne by workers aged 50 and above. This is not very likely to be the case here, given that the correlations between our innovation variables and the wage-bill shares of the various age groups remain unchanged after controlling for employment dynamics at the firm level. However, in order to get a more detailed view on this question, we jointly estimate the impact of $COMP$, $ORGA$ and $INET$ on employment inflows and outflows for all age groups in each firm. If the share of exits is systematically higher for older workers in innovative firms, downsizing and relative separation costs may be important factors, in addition to adaptability problems. In contrast, if part of the effect of innovation goes through hiring opportunities being different across age groups, this will indicate that downsizing does not play a major role in the anti-age bias, and that some skills obsolescence or adaptability problem may be at work.

As mentioned in Section 2, when estimating the share of entries and exits in each age group, we pool our data over 1998-2000. We do so in order to take into account the fact that employment adjustments may take time. One potential problem with this strategy is that, thus doing, we are likely to introduce some noise in our estimates, due to the fact that a number of firms which had not introduced any innovation by 1997 may have done so over 1998-2000. However, such a noise will make us consider as non innovative, firms with an age structure of employment flows very similar to that of our group of innovative firms. This will, if anything, bias our results towards zero.

Results are reported in Table 6. The average impact on employment flows varies according to the type of innovation. Computer use does not seem to affect neither entry nor exit. In contrast, firms using the Internet seem to hire more workers, while new organisational practices would reduce both in and outflows with a stronger effect on the latter, though.

When coming to the age structure of employment flows, our results suggest that new technologies mainly affect hiring opportunities of the various age groups, whereas the impact of organisational innovations is essentially on exits. Computer use positively affects hiring of workers aged 30-39 and the same holds for the Internet with workers aged 20-29. As regards the Internet, its differential impact on workers over 40 is negative. Given that, on average, the Internet tends to enhance inflows, its overall impact on the hiring of workers over 40 is positive,[15] but much (and significantly) less than for younger workers. Last, computer use reduces hiring opportunities for workers aged 40-49. As regards outflows, computer use has no differential impact on the various age groups. The only significant effect comes from the Internet which has a positive impact on exits for workers aged 30 to 39. Regarding new organisational devices, they have no differential impact on the various age groups as far as employment inflows are concerned. In contrast, their differential impact is negative on outflows of workers aged 20-29, whereas it is positive for workers above 50 and, to a lower extent, for those aged 30-39. This means that new work practices reduce exit for younger workers much more than they do for older ones.

[15] The overall impact of innovation on employment flows is the sum of the average effect on the flow and the differential age effect.

Splitting employment flows across gender yields very similar results[16]. IT have a positive impact both on men and women inflows (with computer use being mostly significant for men and the Internet for women). As regards innovative organisational practices, they reduce outflows of younger women much more than for older ones, but have no differential effect across age for men outflows. One interesting point though is that splitting across gender allows us to uncover a differential impact of organisational innovation upon the age structure of inflows for men: positive for the youngest group and negative for the older ones. The pattern of results is not so clear for women but the net impact of organisational innovation upon inflows and outflows remains positive for younger women and negative for older ones.

Overall, the use of new technologies tends to generate much greater entry opportunities for younger workers relative to older ones, while for organisational innovations, the age bias is mainly due to a lower decrease in the number of exits in the older group relative to younger workers.[17] When using new technologies, firms are more reluctant to hire older workers and tend to favour younger ones. This difference in hiring practices towards the various age groups may be due to older workers being less adaptable than younger ones in a fast changing environment.

4 Conclusion

Wage-bill share equations provide an insight of how new technologies and innovative workplace practices affect the optimal age structure of the labour force. From our study, we can draw several conclusions. First, innovative firms tend to be biased against age. They allocate, if anything, a lower share of their wage bill to workers aged 50 and above, while the opposite holds for workers below 40. This holds both for men and women separately. Moreover, this anti-age bias of innovation shows up both in the whole population and within occupational categories. This suggests that skills do not completely protect workers against the labour-market consequences of ageing. Eventually, firms' age structure is affected by innovation both through employment inflows and outflows. New technologies tend to increase hiring opportunities much less for older workers than for younger ones. They even decrease hiring for older workers in

[16]The corresponding tables of results are available from the authors upon request.

[17]One problem with our data is that we identify workers entering or leaving establishments, not firms. So, our measures of employment flows are overestimated, since workers moving from one establishment to another establishment in the same firm are considered as entering and leaving the firm at the same time. However, if we run regressions on the sub-panel of firms with only one establishment, our results are essentially unaffected. In particular, the effect of computer use and of the Internet on the age pattern of hirings is reinforced when estimated on this sub-panel, where flows reflect true hirings or exits from firms. In constrast, the effect of organisational change on exits is not significant any more.

the case of computer use. In contrast, organisational innovations mainly affect exits, which decrease less for older workers than for younger ones. The difference we find in hiring practices between innovative and non-innovative firms towards the various age groups suggests that skills obsolescence or adaptability problems may be partly responsible for the declining employment prospects of older workers.

Our study raises a number of issues. The first one has to do with the specificity of IT and related new work practices. Is the age bias associated with this type of innovation specific to the current technological paradigm or is it to be observed for any type of innovation? Goldin and Katz (1998) show that the skill-technology complementarity also existed in manufacturing at the beginning of the 20th century and that it was related to the adoption of electric motors and continuous process and batch methods. It would be interesting to carry out a similar analysis for older workers. Was the anti-age bias of innovation as strong as it is today at the time when electrical energy started to develop, or was experience a more valuable input in the production process? If older workers suffer from a decrease in the value of their skills when production methods change and if they have difficulty in adapting to new techniques and organisations, it is likely that any major change in technological and organisational methods be biased against age. However, a major difference across innovations lies in the speed with which they develop. This is likely to be crucial as a determinant of the adaptability of older workers. Casual evidence from case studies[18] indeed shows that when they are given enough time, older workers do adapt to changes in their working environment. This suggests that one problem with IT is that their introduction often takes place over a relatively short period of time, at least within individual firms. It would be interesting to see whether, in a context of more progressive changes, associated to different types of innovations, older workers would adapt more easily so that the anti-age bias would end up being milder.

A second issue raised by our study has to do with the transitory or permanent nature of the anti-age bias associated with IT and innovative workplace practices. The policy implications of the shift in employment against older workers observed in innovative firms are, of course, very different if it is a structural, hence permanent, consequence of the introduction of IT or if it arises essentially in a transition period, until workers have learnt about their new work environment. In the latter case, the prediction is that as we will eventually converge towards a new steady state in which the balance between older and younger workers will turn back to be more favourable to the senior workers. This happens if IT require that workers adapt at the moment they are

[18]See Volkoff *et al.* (2000).

introduced because they represent a major change in production methods, but if, once stabilised, they do not require particular adaptability capacities. In this case, younger workers would have a comparative advantage in the initial phase, when IT are adopted, but it would disappear as workers get used to them. In contrast, if IT adoption has induced a move towards a new technological paradigm in which changes are more frequent, then adaptability is likely to be a key determinant of productivity and employability, not only in the transition period, but also in the longer run. In this case, older workers will suffer from a comparative *disadvantage* on a permanent basis. This is actually what suggests recent evidence regarding the demand for experienced workers. Weinberg (2005) finds that the returns to experience have decreased for college graduates (although they have increased among high school graduates). Using a different empirical approach, Abowd *et al* (2005) find even sharper results. They study the impact of a firm's use of innovative technologies upon its demand for two components of human capital: individual ability and experience. They show that firms that intensely use technologies are more likely to use high ability workers, but less likely to use high experience workers. Such evidence is not surprising, given the type of changes that IT have induced in the organisation of work. As underlined by Autor *et al.* (2003), new technologies substitute for workers in performing routine tasks and complement them in performing non routine, problem solving and complex communication tasks. As a consequence, workers are required to perform an increasing variety of activities and to adjust to frequent redefinitions of their tasks. In such a context, adaptability becomes a major input into the production process and the anti-age bias of IT is likely to be more permanent than transitory.

Whether older workers actually suffer from a permanent rather than transitory disadvantage in relation to IT adoption is ultimately an empirical matter. So far, scholars in this field have not been able to investigate this issue due to the fact that IT being quite recent, data series were too short. But, as time will elapse, more information will become available about the time dynamics of IT adoption and of its labour-market consequences. This is a question on which researchers should certainly focus in the coming years, all the more that if, due to adaptability problems, older workers suffer from a long term handicap in the new production process, then life-long learning becomes a first rank priority on the policy agenda.

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Table 1
Frequency of innovative organisational practices
and technological characteristics of firms using them

Number of innovative organisational practices	0	1	2	3	4	5	6
% of firms	14.18	13.31	11.58	10.85	10.56	8.57	6.66
Average computer use	0.50	0.64	0.70	0.75	0.80	0.82	0.89
Average Internet use	0.16	0.27	0.32	0.32	0.42	0.44	0.48

Number of innovative organisational practices	7	8	9	10	11	12	13
% of firms	6.73	5.03	4.40	3.72	2.52	1.18	0.71
Average computer use	0.89	0.87	0.95	0.98	0.98	0.98	0.89
Average Internet use	0.57	0.65	0.64	0.69	0.66	0.73	0.70

Notes:
1. For each number of innovative organisational practices, the first row of each panel provides the proportion of firms using these organisational practices.
2. For each number of innovative organisational practices, the average computer use is defined as the average value of $COMP$ in firms using these organisational practices.
3. For each number of innovative organisational practices, the average Internet use is defined as the average value of $INET$ in firms using these organisational practices.

Table 2
Correlations coefficients between innovation indicators and wage-bill shares by age group

	$ORGA$	$INET$	$COMP$
All workers			
20-29 years old	-0.009	-0.033**	-0.001
30-39	-0.004	0.016	0.040**
40-49	0.044**	0.022	0.011
50-59	-0.029*	-0.009	-0.046**
Men			
20-29 years old	0.037**	-0.056**	0.023
30-39	0.080**	0.001	0.094**
40-49	0.122**	0.041**	0.090**
50-59	0.037**	0.014	0.026
Women			
20-29 years old	-0.074**	0.028*	-0.039**
30-39	-0.116**	0.019	-0.076**
40-49	-0.101**	-0.025	-0.010**
50-59	-0.131**	-0.047**	-0.146**
Managers			
20-29 years old	0.138**	0.215**	0.163**
30-39	0.179**	0.295**	0.231**
40-49	0.137**	0.242**	0.182**
50-59	0.013	0.106**	0.028*
Clerks			
20-29 years old	-0.118**	-0.011	-0.176
30-39	-0.112**	-0.021	-0.019
40-49	-0.070**	0.002	-0.030*
50-59	-0.064**	-0.030*	-0.051**
Blue-collars			
20-29 years old	-0.049**	-0.147**	-0.081**
30-39	-0.137**	-0.251**	-0.166**
40-49	-0.056**	-0.195**	-0.144**
50-59	-0.042**	-0.149**	-0.098**

Notes: 1. Results in the first panel read as follows: the correlation coeffcient between $ORGA$ and the share of workers aged 20-29 in the wage bill is -0.009.
2. Results in the 2nd panel read as follows: the correla--tion coeffcient between $ORGA$ and the share of men aged 20-29 in the overall wage bill is 0.037.
The same reading holds for all panels below.
3. Estimates significant at the 5 (resp. 10) percent level are indicated by ** (resp. *).

Table 2 - followed
Correlations coefficients between innovation indicators and wage-bill shares by age group

	ORGA	*INET*	*COMP*
All workers - Inflows			
20-29 years old	-0.017*	0.048**	-0.001
30-39	-0.093**	-0.016	-0.044**
40-49	-0.110**	-0.043**	-0.082**
50-59	-0.079**	-0.015	-0.046**
All workers - Outflows			
20-29 years old	-0.116**	-0.038**	-0.057**
30-39	-0.122**	-0.045**	-0.064**
40-49	-0.127**	-0.054**	-0.073*
50-59	-0.063**	-0.022**	-0.033**

Notes: Estimates significant at the 5 (resp. 10) percent level are indicated by ** (resp. *).

Table 3
Wage-bill shares by age groups - 1998
JGLS (coefficients x 100)

	Age 20-29	Age 30-39	Age 40-49	Age 50-59
Computer use (COMP)	0.423	1.258^{**}	-0.455	-1.225^{**}
	(0.368)	(0.439)	(0.409)	(0.454)
Internet (INET)	0.392	1.032^{**}	-0.516	-0.908^{**}
	(0.339)	(0.404)	(0.377)	(0.417)
Organisational innovations (ORGA)	0.168^{**}	0.120^{*}	-0.058	-0.230^{**}
	(0.055)	(0.065)	(0.061)	(0.068)
Physical capital	-0.931^{**}	-0.340^{*}	0.402^{**}	0.869^{**}
	(0.167)	(0.199)	(0.186)	(0.206)
Value-added	-0.192	0.055	-0.310	0.457
	(0.259)	(0.309)	(0.288)	(0.320)

Notes:

1. Number of observations: 3,816 firms.
2. Coefficients in this table are estimates corresponding to $ORGA$, $COMP$ and $INET$, the log of physical capital, and of value-added in the joint estimation of the wage-bill share equations for all age groups but the first one in 1998.

Coefficients for workers aged 20 to 29 are estimated using the homogeneity conditions:
$\gamma_j^{20-29} = -(\gamma_j^{30-39} + \gamma_j^{40-49} + \gamma_j^{50-59})$, $j \in J = \{K; VA;\ COMP, INET, ORGA\}$

3. Basic controls include four size and five industry dummies as well as the log of relative wages (i.e. wages of all age groups relative to the 20-29 years old)
4. Estimated standard errors asymptotically robust to heteroskedasticity are reported in parentheses. Standard errors for the reference group (20-29 years old) are calculated using the Delta method. Estimates which are significant at the 5 (resp. 10) percent level are indicated by ** (resp. *).

Table 4
Wage-bill shares by age and gender group - 1998
JGLS (coefficients x 100)

	Men				
	Men	Age 20-29	Age 30-39	Age 40-49	Age 50-59
Computer use	0.502**	-0.200	1.112**	-0.190	-0.733*
	(0.180)	(0.301)	(0.373)	(0.357)	(0.391)
Internet	-0.657**	0.138	0.468	-0.485	-0.120
	(0.165)	(0.276)	(0.342)	(0.327)	(0.358)
Organisational innovations	-0.015	0.131**	0.125*	-0.048	-0.207**
	(0.027)	(0.045)	(0.056)	(0.053)	(0.058)
Physical capital	0.862**	-1.251**	-0.076	0.750**	0.577**
	(0.082)	(0.137)	(0.170)	(0.162)	(0.178)
Value-added	0.406**	-0.464**	0.009	0.045	0.410
	(0.125)	(0.208)	(0.258)	(0.247)	(0.270)
	Women				
	Women	Age 20-29	Age 30-39	Age 40-49	Age 50-59
Computer use	-0.502**	0.512**	0.255	-0.242	-0.526**
	(0.180)	(0.180)	(0.187)	(0.205)	(0.178)
Internet	0.657**	0.216	0.645**	-0.318*	-0.542**
	(0.165)	(0.165)	(0.172)	(0.188)	(0.163)
Organisational innovations	0.015	0.027	0.000	0.032	-0.059**
	(0.027)	(0.027)	(0.028)	(0.031)	(0.027)
Physical capital	-0.862**	0.302**	-0.245**	-0.349**	0.292**
	(0.082)	(0.082)	(0.085)	(0.093)	0.081
Value-added	-0.406**	0.218*	0.133	-0.544**	0.193
	(0.127)	(0.126)	(0.131)	(0.142)	(0.125)

Notes: 1. Number of observations: 3,816 firms.

2. The overall impact of innovation on the wage-bill share of an age-by-gender group is the sum of the average gender effect and the differential age effect.

The average gender effect is calculated as the average over the four age groups, e.g.
$\widehat{\widehat{\gamma}}_{ORGA}^{men} = \frac{1}{4}\sum(\widehat{\gamma}_{ORGA}^{20-29,men} + \widehat{\gamma}_{ORGA}^{30-39,men} + \widehat{\gamma}_{ORGA}^{40-49,men} + \widehat{\gamma}_{ORGA}^{50-59,men})$
The differential age effects are the difference between the estimates and
the average gender effects, e.g. $\widehat{\widehat{\gamma}}_{ORGA}^{30-39,men} = \widehat{\gamma}_{ORGA}^{30-39,men} - \widehat{\widehat{\gamma}}_{ORGA}^{men}$
Within a gender category, age differential effects therefore add up to zero.

3. Controls include four size and five industry dummies

Table 5

Wage-bill shares by age and occupational groups - 1998

JGLS (coefficients x 100)

			Managers		
	Managers	Age 20-29	Age 30-39	Age 40-49	Age 50-59
Computer use	1.517**	-0.531**	1.637**	0.406	-1.511**
	(0.178)	(0.179)	(0.274)	(0.261)	(0.309)
Internet	2.297**	-0.896**	1.612**	0.208	-0.924**
	(0.164)	(0.164)	(0.251)	(0.239)	(0.283)
Organisational innovations	0.036	0.075**	0.173**	-0.041	-0.206**
	(0.027)	(0.027)	(0.041)	(0.039)	(0.046)
Physical capital	0.133	-0.401**	-0.298**	0.273**	0.426**
	(0.081)	(0.082)	(0.125)	(0.119)	(0.140)
Value-added	1.548**	-1.038**	0.494**	0.5180**	0.026
	(0.124)	(0.124)	(0.190)	(0.181)	(0.124)
			Clerks		
	Clerks	Age 20-29	Age 30-39	Age 40-49	Age 50-59
Computer use	0.066	0.121	0.166*	-0.101	-0.186**
	(0.069)	(0.080)	(0.093)	(0.090)	(0.087)
Internet	0.146**	0.127*	0.098	-0.017	-0.208**
	(0.063)	(0.074)	(0.085)	(0.082)	(0.080)
Organisational innovations	-0.042**	0.016	-0.003	-0.016	0.003
	(0.010)	(0.012)	(0.014)	(0.013)	(0.013)
Physical capital	0.036	-0.084**	0.005	0.072*	0.007
	(0.031)	(0.036)	(0.042)	(0.041)	(0.040)
Value-added	-0.024	-0.055	0.075	-0.100	0.080
	(0.048)	(0.056)	(0.064)	(0.062)	(0.061)
			Blue-Collars		
	Blue-collars	Age 20-29	Age 30-39	Age 40-49	Age 50-59
Computer use	-1.583**	0.723**	-0.426	-0.736**	0.438*
	(0.195)	(0.285)	(0.290)	(0.288)	(0.251)
Internet	-2.443**	1.122**	-0.598**	-0.994**	0.469**
	(0.179)	(0.261)	(0.266)	(0.264)	(0.230)
Organisational innovations	0.006	0.067	-0.046	0.041	-0.062*
	(0.029)	(0.042)	(0.043)	(0.043)	(0.037)
Physical capital	-0.169	-0.465**	-0.028	0.057	0.436**
	(0.089)	(0.129)	(0.132)	(0.131)	0.114
Value-added	-1.524**	0.848**	-0.427**	-0.917**	0.497**
	(0.135)	(0.197)	(0.201)	(0.199)	(0.173)

Notes: 1. Number of observations: 3,816 firms.

2. The overall impact of innovation on the wage-bill share of an age-by-occupation group is the sum of the average occupation effect and the differential age effect.

The average occupational effect is calculated as the average over the four age groups, e.g.

$\widehat{\widehat{\gamma}}^{clerk}_{ORGA} = \frac{1}{4}\sum(\widehat{\gamma}^{20-29,clerk}_{ORGA} + \widehat{\gamma}^{30-39,clerk}_{ORGA} + \widehat{\gamma}^{40-49,clerk}_{ORGA} + \widehat{\gamma}^{50-59,clerk}_{ORGA})$

The differential age effects are the difference between the estimates and

the average coefficient effects, e.g. $\widehat{\widehat{\gamma}}^{30-39,clerk}_{ORGA} = \widehat{\gamma}^{30-39,clerk}_{ORGA} - \widehat{\widehat{\gamma}}^{clerk}_{ORGA}$

Within an occupational category, coefficients for age groups therefore add up to zero.

3. Controls include four size and five industry dummies.

Table 6
Employment inflows and outflows by age group
JGLS (coefficients x 100)

Inflows					
	Inflows	Age 20-29	Age 30-39	Age 40-49	Age 50-59
Computer use	-0.409	0.424	0.513**	-0.769**	-0.168
	(0.346)	(0.352)	(0.203)	(0.203)	(0.238)
Internet	0.780**	0.902**	0.084	-0.584**	-0.403*
	(0.314)	(0.319)	(0.184)	(0.184)	(0.216)
Organisational innovations	-0.091*	0.024	-0.033	0.037	-0.027
	(0.051)	(0.052)	(0.030)	(0.030)	(0.035)
Physical capital	-0.983**	-0.069	0.014	-0.180*	0.235**
	(0.164)	(0.167)	(0.096)	(0.096)	(0.113)
Value-added	-2.011**	-0.277	0.022	-0.096	0.351*
	(0.276)	(0.281)	(0.162)	(0.162)	(0.190)

Outflows					
	Outflows	Age 20-29	Age 30-39	Age 40-49	Age 50-59
Computer use	-0.107	-0.087	0.242	-0.166	-0.011
	(0.405)	(0.331)	(0.210)	(0.208)	(0.273)
Internet	0.411	-0.258	0.411**	0.053	-0.206
	(0.339)	(0.278)	(0.176)	(0.172)	(0.233)
Organisational innovations	-0.138**	-0.162**	0.052*	0.036	0.073*
	(0.060)	(0.049)	(0.031)	(0.031)	(0.040)
Physical capital	-0.686**	-0.061	-0.210**	-0.226**	0.497**
	(0.192)	(0.157)	(0.100)	(0.098)	(0.129)
Value-added	-2.559**	-0.765**	0.077	0.283*	0.404*
	(0.324)	(0.265)	(0.168)	(0.166)	(0.218)

Notes: 1. Number of observations: 9,573 firms*year.
2. Dependent variables are the shares of entrants and of workers leaving the firm among the total number of workers in each age group.
3. The overall impact of innovation on employment flows is the sum of the average effect on the flow and the differential age effect.
Coefficients $\widehat{\theta}$ in this table are calculated from the estimates $\widehat{\beta}$ of $ORGA$, $COMP$ and $INET$ in the joint estimation of employment inflows and outflows for each age group.
Average effects on employment flows are the averages over the four age groups, e.g.
$\widehat{\theta}^{HIRE}_{INNOV} = \frac{1}{4}\sum \widehat{\beta}^{a',HIRE}_{INNOV}$ for $a' \in \{1...4\}$, and $\widehat{\theta}^{EXIT}_{INNOV} = \frac{1}{A}\sum \widehat{\beta}^{a',EXIT}_{INNOV}$
Differential age effects are the difference between the estimates and the average effects on the corresponding employment flows, e.g.
$\widehat{\theta}^{30-39,HIRE}_{INNOV} = \widehat{\beta}^{30-39,HIRE}_{INNOV} - \frac{1}{4}\sum \widehat{\beta}^{a',HIRE}_{INNOV}$ (where $INNOV$ = $ORGA$, $COMP$ or $INET$). Within each employment-flow category, differential age effects add up to zero.
4. Controls dated $(t-1)$ include the log of the value-added, of the stock of capital and of relative wages along with the employment shares of all age groups, and dummies for 5 size groups, 6 industries and 3 years.

Appendix Table
(Descriptive statistics)

	20-29	30-39	40-49	50-59	All ages
Average wage-bill share					
All occupations	0.14	0.31	0.33	0.22	100
	(0.09)	(0.11)	(0.10)	(0.11)	
including:					
Managers	0.04	0.12	0.14	0.12	0.42
	(0.04)	*(0.09)*	*(0.09)*	*(0.09)*	*(0.20)*
Clerks	0.02	0.03	0.03	0.02	0.08
	(0.02)	*(0.03)*	*(0.03)*	*(0.03)*	*(0.07)*
Blue-collars	0.09	0.17	0.16	0.09	0.50
	(0.08)	*(0.10)*	*(0.10)*	*(0.07)*	*(0.21)*
Men	0.10	0.23	0.24	0.17	0.74
	(0.08)	*(0.11)*	*(0.11)*	*(0.11)*	*(0.21)*
Women	0.04	0.08	0.09	0.05	0.26
	(0.05)	*(0.08)*	*(0.09)*	*(0.06)*	*(0.12)*
Inflows (average share of entrants)					
	0.35	0.14	0.11	0.08	0.16
	(0.20)	(0.16)	(0.15)	(0.15)	(0.16)
Outflows (average share of workers leaving the firm)					
	0.28	0.15	0.12	0.15	0.19
	(0.21)	(0.17)	(0.17)	(0.19)	(0.21)

Notes: 1. For inflows and outflows, the average shares of workers entering or leaving the firm are computed using years 1998, 1999 and 2000.
2. Standard deviations are in parentheses